Machine Learning Model for Offensive Speech Detection in Online Social Networks Slang Content

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Abstract: - The majority of the world's population (about 4 billion people) now uses social media such as Facebook, Twitter, Instagram, and others. Social media has evolved into a vital form of communication, allowing individuals to interact with each other and share their knowledge and experiences. On the other hand, social media can be a source of malevolent conduct. In fact, nasty and criminal activity, such as cyberbullying and threatening, has grown increasingly common on social media, particularly among those who use Arabic. Detecting such behavior, however, is a difficult endeavor since it involves natural language, particularly Arabic, which is grammatically and syntactically rich and fruitful. Furthermore, social network users frequently employ Arabic slang and fail to correct obvious grammatical norms, making automatic recognition of bullying difficult. Meanwhile, only a few research studies in Arabic have addressed this issue. The goal of this study is to develop a method for recognizing and detecting Arabic slang offensive speech in Online Social Networks (OSNs). As a result, we propose an effective strategy based on the combination of Artificial Intelligence and statistical approach due to the difficulty of setting linguistic or semantic rules for modeling Arabic slang due to the absence of grammatical rules. An experimental study comparing frequent machine learning tools shows that Random Forest (RF) outperforms others in terms of precision (90%), recall (90%), and f1-score (90%).

Key-Words: - Cyberbullying; offensive speech detection; Arabic social media; Classifications, Machine Learning, Social Network, Arabic slang.

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1 Introduction

In the last decade, the use of social media in the world is in exponentially grown. In fact, more than half of the world's population (about 4 billion people), use social media such as Facebook, Twitter, Instagram, etc. These tools are becoming a very important communication means allowing people to connect to each other and exchange their knowledge and experiences. Unfortunately, social media are also a source of intellectual extremism, cyberbullying, and violation that can be normal or death threats, racism, insults, bullying, or any kind of terrorist acts. The detection of social medial threats is a challenging problem due to the following:

- There are an exponential amount of information, tweets, posts, comments, instant chat, and blogs on social media,
- There are few types of research related to Arabic languages in this field,
- Most of the Arabic users are using the local dialect instead of the standard Arabic language.

Consequently, in this research work, we intend to propose an efficient method based on a combination of Artificial Intelligence techniques and statistical features since it is very difficult to set linguistic or semantic rules for modeling Arabic slang because there is no clear grammatical rule. The proposed approach will use the statistical approach in order to ensure optimal performance for the system. In the next section, we highlight and discuss the most relevant proposed work in this context where AI tools have been combined with many types of data set extracted from the relevant social network (YouTube, Facebook, Twitter, and Instagram) in order to deal with social media threats.

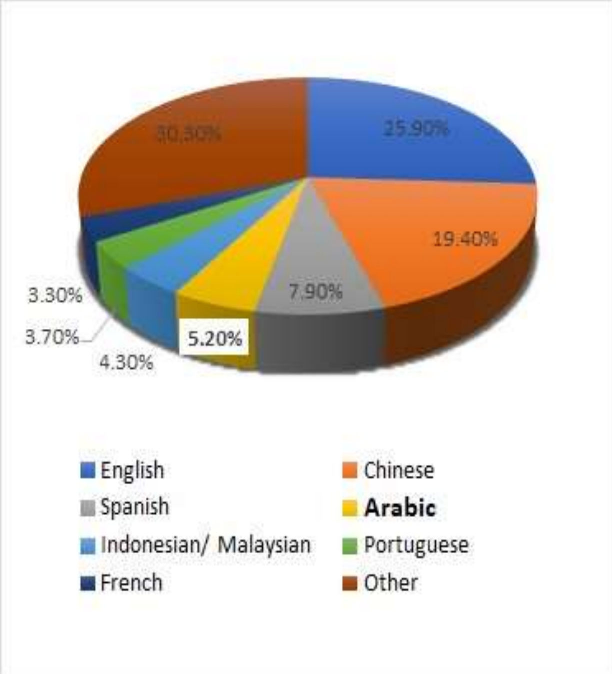

Fig. 1: Most common languages used on the internet

1.1 Motivation

Fig. 1 outlines recent statistics, [1], studying the most common language used on the internet, showing that Arabic is in the fourth rank with 5.20% of the total Internet content. This important average is not followed by similar research efforts to analyze and study this language. In addition, a part of Internet users is preferring Arabic slang which is issued from classical Arabic in addition to other natural languages. This fact complicates content analysis and recognition.

On the other hand, the most important amount of Arabic internet content is located in social networks. Although their advantages are to connect people by communicating, collaborating, and exchanging ideas, social network is becoming a source of cyberbullies, offensive speech, and threats. These problems are hard to be followed and controlled manually. This makes the task of analyzing the content so important and challenging due to previously mentioned conditions in Arabic languages.

1.2 Contribution

The keys contributions of this work are:

1. To propose a purely statistical approach for detecting hate speech and offensive social networks in Arabic slang content since it is very difficult to set grammatical rules for it.
2. To prepare a dataset containing Arabic slang tweets and posts to be fit for classification use based on the statistical approach defined previously.
3. To deploy a set of machine learning approaches which are: Logistic Regression (LR), Decision Tree (DT), k-nearest neighbors' algorithm (k-NN), Linear Discriminant Analysis (LDA), Multinomial Naive Bayes (MNS), Gaussian Naive Bayes (GNB), Support Vector Machines (SVM), Random Forest (RF), and Neural Network (NN).
4. To compare the previously mentioned techniques and extract the optimal performance to detect cyberbullying, hate speech, and offensive Arabic slang content.

1.3 Paper Organization

The remainder of this paper is organized as follows: Section 2 outlines the related works. In section 3 we describe the proposed model. Section 4 presents the used dataset and discusses the experimental results. Finally, the conclusion is given in section 5.

2 Related works

Intellectual extremism detection is considered a recent direction of research in the Computer Science domain. In fact, the extraction of emotions, opinions, and sentiment from textual content has emerged with the rise of the social network. In the following paragraphs, we provide a brief description of the main approaches used for intellectual extremism and cyberbullying detection with a focus on those based on Text Analysis.

Huang et al., [2], claimed that textual features are not enough for efficiently detecting intellectual extremism and cyberbullying. For this reason, they proposed to integrate structural social network features in order to improve the accuracy of the system. The proposed approach analyzes the structure between the user and several structural features such as the number of friends, network embeddedness, and relationship centrality.

Nandhini and Sheeba, [3], provided an approach based on fuzzy logic and a genetic algorithm in order to recognize cyberbullying words in social media. For learning the classification algorithms, the authors extracted two types of features: linguistic (PoS) and numerical (frequency). The authors used NLP tools for the phase of text preprocessing and the phase of linguistic feature extraction.

In the same context, Nahar et al. proposed a Machine Learning-based approach for detecting abusive content on social networks, [4]. They used a semi-supervised learning technique for decreasing the number of training samples. For the classification phase, the authors applied a fuzzy SVM algorithm. As mentioned by the authors, this

technique is mainly designed for solving many problems related to cyberbullying detection in real-world situations like noisy and imbalanced data.
The work of Lee et al. applied Sentiment Analysis techniques to messages and posts on Twitter, [5].
Practically, the authors proposed an auto-detection model that used linguistic features, readability (education level, age, and social status), sentiment score, and information about the friendship network of the target for predicting tweets containing harassment or cyberbullying. For the classification task, this approach applied Three Machine learning algorithms: k-nearest neighbors, support vector machine, and decision tree.
Alotaibi et al. introduced a Deep Learning- based technique for detecting offensive and aggressive behavior, [6]. For cleaning the text and extracting linguistic features, the authors utilized Natural Language Tools. Multichannel deep learning was used for the classification phase, which consists of three modules: bidirectional gated recurrent unit (BiGRU), transformer block, and convolutional neural network (CNN).
Akhter et al. proposed a Machine learning-based model for detecting cyberbullying on social media, [7], the model is learned through linguistic features (PoS) extracted from the corpora using NLP tools. In order to classify textual messages into three classes: Shaming, Sexual harassment, and Racism. For the classification phase, the system used a hybrid model that combined a Multinomial Naïve Bayes classifier and fuzzy logic.
In a different approach, [8], the authors coupled intelligence techniques with specific web technology problems in order to combat cyberbullying. This approach used text analysis and data mining techniques for the classification of posts on social media.
In the same context, Haidar et al. applied Machine Learning algorithms (Naïve Bayes and SVM) and NLP tools to the Arabic language, [9]. A similar approach proposed by the same authors, [10], was applied to the Arabic language and provided modest results.
Mohaouchane et al. were basing the deep learning approach, [11], to detect offensive Language in the content of Arabic social media. Motivated by the problem of negative effects on users, the authors try to discover automatically hate speech, demeaning comments, or verbal attacks. They propose to use a set of deep learning tools on a labeled YouTube comments dataset. Although the accuracy results are encouraging, there is a lack of comparison with similar papers.
Omar et al. proposed a comparison between a set of machine and deep learning techniques, [12], which have been used to discover hate speech in Arabic Online Social Networks (OSNs). The data has been collected from a diversity of the most frequent social networks (Twitter, Instagram, YouTube, and Facebook). The authors conducted an experimental study using a set of two deep learning architectures and twelve machine learning algorithms. Based on this study, they found that Recurrent Neural Network (RNN) performed better than the other reaching 98.7% accuracy.
Husain and Uzuner, [13], deal with the detection of offensive language in OSN Arabic content. The authors discuss and compare important proposed techniques for studying this serious problem. They concentrate on studying contributions mixing between Natural Language Processing (NLP) and machine learning models. After studying the state-of-the-art in this field, the authors conclude that still needs gaps and limitations to be treated. So, further research effort has to develop novel benchmark resources besides investigating more on the feature extraction techniques and pre-processing.
ALBayari et al. study the problem of cyberbullying, [14]. They show that most previous studies are concentrating on the English language. They intend to propose a review of classification methods used to discover cyberbullying in Arabic texts. They found gaps related to the few numbers of research in that field in addition to the limitations linked to the datasets themselves. Moreover, the majority of proposed contributions to automatically detect Arabic cyberbullying are based on Twitter, and most of them are using the SVM classifier or CNN.

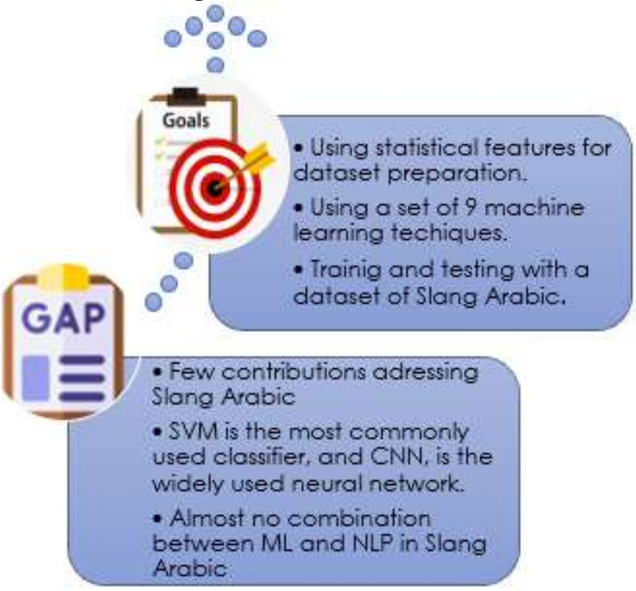

Fig. 2: Existing gaps and the goals of our paper

This literature review conducts us to summarize gaps and limitations and link them to the goals of our paper in Fig. 2.

3 Proposed Model

In this section, we make a general overview of machine learning and the used classification techniques. In addition, we outline how the dataset was prepared.

3.1 Machine Learning Overview

Machine Learning (ML) is a subset of Artificial Intelligence (AI) tools. AI is a simulation of human intelligence. ML is linked to the use of probabilistic mathematical formulas by machines to "learn" and decide the output after exercising on a dataset of inputs.

The basic ML steps are (1) Data collection, (2) Data preparation, (3) Model training, (4) Model evaluation and finally (5) Model Tuning.

There are essentially 4 types of ML models:

- Supervised Learning Models: working with a labeled dataset like Neural Networks, SVM, Decision Trees, and Naïve Bayes, [15]. A supervised learning algorithm aims to model connections and dependencies between the input features and the target prediction output.
- Unsupervised Learning Models: which predict outputs with no labels like Principal Component Analysis (PCA), [16,17], for data reduction K-means for clustering. These algorithms attempt to employ techniques on the input data to find patterns, aggregate and summarize the data points, recognize patterns, and derive relevant insights that help users understand the data better.
- Semi-Supervised Learning Models: This is a hybrid approach from the previous two types, like Generative Adversarial Network (GAN). These techniques take advantage of the fact that, despite the unlabeled data's unknown group memberships, this data contains crucial details about the group parameters.
- Reinforcement Learning Models: is very close to human learning based on driving the learning process where a learner would work better, like Q-learning. This technique tries to take decisions that would maximize the reward or minimize the risk utilizing observations acquired from the interaction with the environment. The agent, a reinforcement learning algorithm, iteratively continually learns from its surroundings, [18].

3.2 Execution Process

In our proposed model, the execution process is performed essentially in three phases as shown in Fig. 3:

Phase1:

Preparing the dataset by using a statistical approach to create features describing the list of tweets, comments, and posts. In addition to making a fair distribution of classes to guarantee realistic behavior and acceptable results.

Phase2:

Using 9 relevant machine and deep learning tools for training and testing based on the previous dataset with the aim of predicting tweets, comments, and posts.

Phase3:

Compare and discuss the result of the technique used previously. The comparison will be based on precision, F1-score, and Recall. In case the result is not satisfactory, go to phase 2.

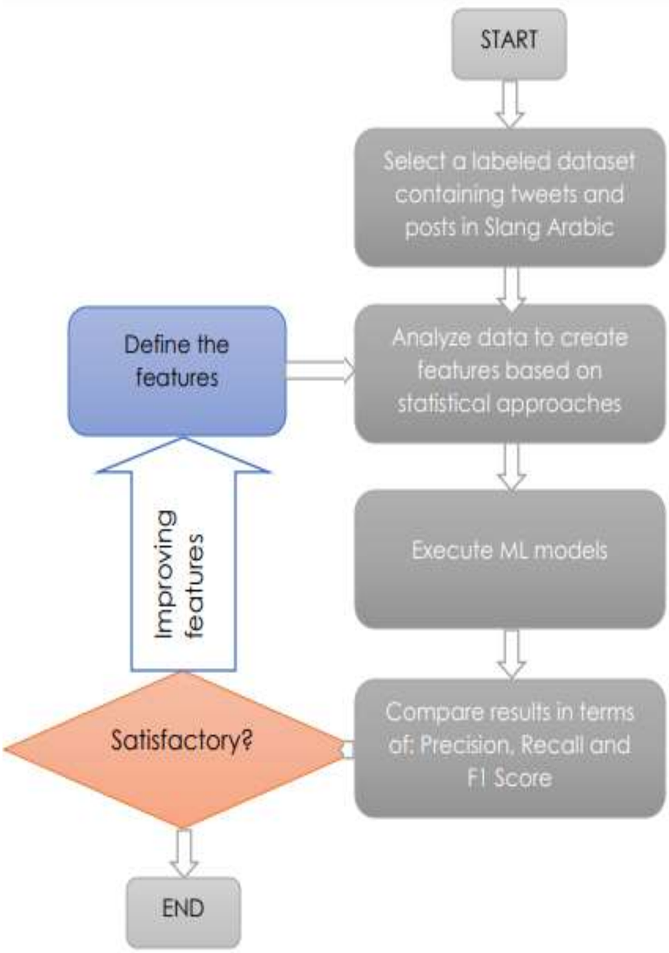

Fig. 3: Phases of the proposed method

3.3 Features Preparation

In order to detect hate and offensive speech in Arabic slang tweets, posts, and comments, we propose Machine Learning methods using statistical features, [19], [20]. This choice is motivated by many reasons such as, it is very difficult to set linguistic or semantic rules for modeling Arabic slang since it doesn't follow any grammatical rules. Furthermore, the Slang language is very local even in the same country. For all these mentioned reasons, we choose to use a purely statistical approach.

As we have mentioned, our approach used a set of numerical features that will be integrated into Machine Learning models. Table 1 presents the used statistical features.

Table 1. Used features

Feature	Explanation
words_number	Number of words in the tweet
Char_number	Number of characters in the tweet
CRLF	CR and LF are control characters that are used to mark a line break in the tweet
retweet_number	the number of retweets
Emoticons	An emoticon is a representation of a human facial expression using only keyboard characters such as letters, numbers, and punctuation marks.
Emojis	An emoji is an image small enough to insert into text that expresses an emotion or idea
question_mark	?
interrogation_mark	!
dot_mark	Full stop.
Hashtag	The hashtag is used to highlight keywords or topics within a Tweet
URL	Uniform Resource Locator

4 Experimental Study

This section provides an experimental study for evaluating our proposed model. In fact, the extracted statistical features will be integrated into a set of 9 well-known Machine Learning:

- Logistic Regression: it is a classification model rather than a regression model mainly (despite its name) used for binary and linear classification problems, [21].
- Decision Tree: it provides a classification and predictive model that can be easily graphically presented. This model has the ability for handling numerical and categorical data, [22].
- k-Nearest Neighbors (KNN): This learning model stores all available data points (examples) and classifies new data points based on similarity measures, [23].
- Linear Discriminant Analysis (LDA): it is a very common technique for dimensionality reduction problems as a pre-processing step for machine learning and pattern classification applications, [24].
- Multinomial Naive Bayes: it predicts the tag of an observation, such as a word or a frequency or PoS, using the Bayes model. It calculates each tag's likelihood for a given observation and provides the tag with the highest chance, [25].
- Gaussian Naive Bayes: Naive Bayes is a group of supervised machine learning classification algorithms based on the Bayes theorem. It is a simple technique for constructing classifiers: models that assign class labels to problem instances, [26].
- Support Vector Machine (SVM): it is a supervised machine learning model that can be used for classification and regression problems. However, the support vector machine is mathematically complex and computationally expensive, [27].
- Random Forest: Random Forest is a computationally efficient technique that can operate quickly over large datasets, [28].
- Neural Network: it is inspired by the sophisticated functionality of human brains where hundreds of billions of interconnected neurons process information in parallel, [29].

4.1 Dataset Description

In this work, we use an Arabic slang dataset named OSACT2020-shared Task. This dataset contains 6964 tweets, comments, and posts that are manually annotated for both classes: offensiveness (labels are: OFF or NOT_OFF) and hate speech (labels are: HS or NOT_HS). All information about this dataset is available in Table 2.

Table 2. Distribution of different classes in the OSACT2020-dataset

Classes	Number of tweets	Ratio	Example
OFF	1323	19%	انت يا طفيلي يا كائن هلامي رخوي وحيد النواة ايش دخلك!!
NOT_OFF	5641	81%	يا سلام يا سلام.. صح لسانك يا سعود مدرسة ونتعلم فيها
HS	348	5%	الله يقلعكم يالبدو يا مجرمين يا خراب المجتمعات
NOT_HS	6616	95%	يا صباح الورد يا ابو دعيج 🌹 😊

As shown in Table 2, the distribution of classes in the dataset is imbalanced. For instance, the ratio of HS class is 5% which is considered a minority in the dataset. For this reason, we have handled this issue using SMOTE algorithm, [30], which is an oversampling technique where the synthetic samples are generated for the minority class. For this purpose, we separated the two classes (HS and OFF) into two different features file. Then, we applied the SMOTE algorithm on each file which provide the following balanced distribution (Table 3):

Table 3. New classes distribution after applying SMOTE algorithm

Classes	Number of records	Ratio	Total number
OFF	1974	50%	3948
NOT_OFF	1974	50%	
HS	2360	50%	4720
NOT_HS	2360	50%	

4.2 Results

The classification results of the set of Machine Learning models applied to the class HS/NOT_HS are shown in Fig. 4 and Table 4. As we can notice, Random Forest and Decision Tree models outscore all the other models with an F1-score of 0.9 and 0.88, respectively. On the other hand, Gaussian Naive Bayes and SVM models provide the worst results with an F1-score of 0.61 and 0.69, respectively.

In conclusion, a Precision and a Recall of 0.9 are considered very good results due to the huge linguistic challenges confronted when extracting Hate speech from documents in Arabic Slang and using only statistical features.

Table 4. Comparison between ML models for HS/NOT_HS class. The best results are shown in bold

ML Models	Precision	Recall	F1-score
Logistic Regression	0.79	0.79	0.79
Decision Tree	0.88	0.88	0.88
KNN	0.84	0.83	0.83
Linear Discriminant Analysis	0.78	0.78	0.78
Multinomial Naive Bayes	0.76	0.74	0.74
Gaussian Naive Bayes	0.71	0.64	0.61
SVM	0.73	0.7	0.69
Random Forest	**0.9**	**0.9**	**0.9**
Neural Network	0.85	0.85	0.85

Regarding the class OFF/NOT_OFF, classification results are very similar to the first class. As shown in Fig. 5 and Table 5, Random Forest and Decision Tree models are still the best and outscore all the other in the three-evaluation metrics with an F1-score of 0.75 and 0.72, respectively. Also, Gaussian Naive Bayes and SVM provide the worst results for this class with an F1-score of 0.53 and 0.61 respectively.

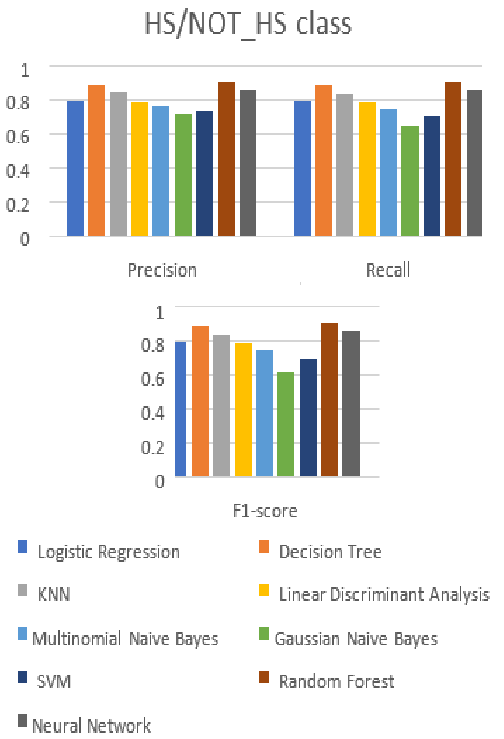

Fig. 4: Evaluation of ML models on HS/NOT_HS class

The main interpretation that can be deduced from these results is that the performance of the proposed model decreased when handling offensive speech versus hate speech. This result can be explained by the fact that offensive speech is more complex and difficult compared with hate speech and need more sophisticated techniques than using simple statistical features. Although statistical features are simple to model and extract from textual content and make the approach independent from any language, they are incapable to recognize semantic relations and need to be combined with semantic knowledge, such as ontologies, [31], [32], [33].

Table 5. Comparison between ML models for OFF/NOT_OFF class. The best results are shown in bold

ML Models	Precision	Recall	F1-score
Logistic Regression	0.71	0.71	0.71
Decision Tree	0.72	0.72	0.72
KNN	0.71	0.7	0.7
Linear Discriminant Analysis	0.7	0.7	0.7
Multinomial Naive Bayes	0.7	0.69	0.69
Gaussian Naive Bayes	0.59	0.56	0.53
SVM	0.61	0.61	0.61
Random Forest	**0.75**	**0.75**	**0.75**
Neural Network	0.72	0.72	0.71

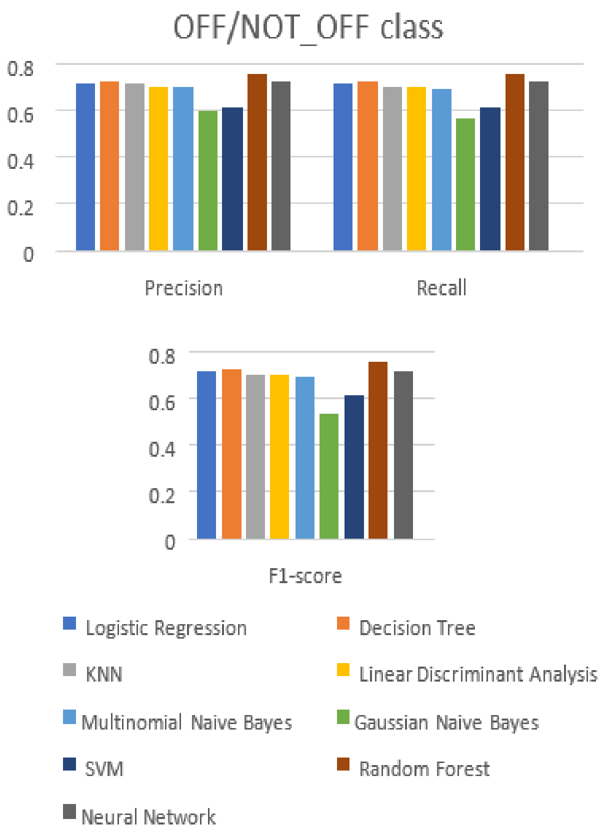

Fig. 5: Evaluation of ML models on HS/NOT_HS class

5 Conclusion

The use of social media is becoming one of day practical habits. As a source of news, ideas exchanging and communications, it is also a source of serious problems like messages of hate and cyberbullying. Meanwhile, the Arabic language is ranked in the 4th place of most commonly used language in internet live content. In return, few research works are addressing this problem in the context of the Arabic language and insufficient research works are dealing with this issue in Arabic slang.

All of that motivates us to propose, in this paper, a purely statistical approach for detecting and predicting cyberbullying, hate speech, and offensive tweets, comments, and posts. Our proposed methods provided good results with a prepared Arabic slang dataset. In fact, results show that our method provided the optimal performance when using Random Forests and Decision Trees as classification models.

In future works, we plan to improve the detection results by working more on the dataset. This can be performed by integrating (Natural Language

Processing) NLP rules with the statistical approach for data preparation.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Fethi Fkih wrote the original draft of the paper and carried out the simulation, the formal analysis, and the optimization.

Tarek Moulahi has defined the methodology, and reviewed, and edited the paper.

Abdulatif AlAbdulatif was responsible for the project administration and the funding acquisition.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.